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Linear and nonlinear TAR panel unit root analyses for solid biomass energy supply of European countries

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ABSTRACT

Biomass is one of the major sources of renewable energy in the World. This paper aims at observing primary biomass energy supply in some EU countries within periods1971–2009 and 1982–2009. Following related two panel data sets for biomass in EU, this work employs linear models and nonlinear threshold autoregression (TAR) models to test linearity against nonlinearity and nonstationarity against stationarity. If nonlinearity is found, then, the next step is to search transition variable and threshold value of the panel data sets. This paper eventually has the purpose to reveal if EU countries converge in the production of biomass in a linear form or nonlinear form. Findings show that panel of Austria, Denmark, Finland, France and Portugal follows nonlinear process and reaches partial convergence in per million primary solid biomass energy supply. However, the involvement of Belgium, Greece, Norway, Poland and Sweden to the panel yields linearity and divergence. One may suggest policy makers of EU and/or OECD, upon conclusion of this paper, to revise their energy policies to stimulate both production and consumption of biomass energy source.

Contents

1. Introduction

Renewable energy sources are solid biomass, biogas, hydropower, renewable industrial and municipal waste, geothermal, solar, wind, tide, wave and ocean, respectively (IEA [1]). Renewable energy alternatives meet 14% of total world energy consumption and, among others, the share of biomass is 62.1% of total renewals in 1995 (Demirbas [2], Victor and Victor [3]). In terms of 2008, IEA [4] statistics reveal that municipal waste, industrial waste, primary solid biomass, biogas, liquid biofuels, geothermal, solar thermal, hydro, solar photovoltaics, tide, wave and ocean, and wind produce 3.851.156 GWh electricity in the World. The primary solid biomass of 162.825 GWh accounts for 4.22% of total renewable gross electricity generation (IEA [4]). IEA [4] also indicates that municipal waste, industrial waste, primary solid biomass, biogas, liquid biofuels, geothermal and solar thermal produce total gross heat of 632801 TJ in the World and that primary solid biomass corresponds to 51.18% of total renewable gross heat production in 2008. The solid biomass accounts for, on the other hand, 6.89% of total renewable gross electricity generation and 53.35% of total renewable gross heat production, respectively, in OECD Europe in 2008 (IEA [5]). Solid biomass

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generates 1.3% of total electricity production in the World in terms of 2006, and it is expected to increase its share from 1.3% to 3–5% by 2050 (IEA [6]).

Biomass keeps its priority in providing countries with energy supply. Throughout its importance to reduce the consumption of fossil fuels, the biomass is expected to be used intensively for transportation (Sagar and Kartha [7]). Biomass is strong candidate in production of electricity, as well. That is why biomass is fundamental to environment in which CO_2 emission is reduced to desired level (Bauen et al. [8]). While biomass can be used in production of electricity, heat and fuel for transportation, it has some barriers such as production costs, conversion efficiency, transportation cost, feedstock availability and lack of supply logistic (IEA [6]). One may expand the list of seminal works emphasizing on importance of biomass in the World in terms of clean environment and efficient usage of energy resources as in Paine et al. [9], Grahn et al. [10], Berglund and Börjesson [11], Caputo et al. [12], Radetzki [13], European Climate Foundation [14], Azar et al. [15], Martinsen et al. [16] and Vargas et al. [17].

This paper mainly concerns the behavior of biomass energy supply in EU countries. The basic purpose of this work is to reveal if EU converges in producing biomass through time following linear or nonlinear equations. Economics literature and/or energy economics literature use intensively classical linear regression models to reach best linear unbiased estimators. However, true data generating process may suggest that related time series may follow nonlinear process. Therefore, considering the possibility of nonlinearity, in economics literature, testing for linearity and/or nonlinearity becomes one of greatest interests to researchers within especially last two-three decades. The two most common nonlinear approaches in economics modeling are Markov-switching (MS) models and Threshold autoregressions (TAR) models. The superiority of these approaches against linear counterparts comes from their statistical properties: (i) they concern regime shifts in estimating procedure, and (ii) they follow nonlinear form(s) in estimating related equation(s). One can find basic MS analyses in details, for instance, in Hamilton [18,19], Engel and Hamilton [20], Goodwin [21], Krolzig [22,23], Jeanne and Masson [24], Lam [25], Frömmel et al. [26], Ribeiro and Pereira [27], Liu and Mumtaz [28] and others. Threshold autoregression (TAR) model is mainly developed by Tong [29,30,31], Tong and Lim [32], Tsay [33], Hansen [34], Strikholm and Terasvirta [35], Beyaert and Camacho [36] and others. Although MS and TAR model have some similar methodologies, they differ at two points: (i) TAR needs to assign a transition variable whereas MS does not, and (ii) MS requires less prior information than the TAR does (Deschamps [37]).

The motivation of this paper lies in two points. First, there are relatively few papers which follow nonlinear MS and/or TAR models in literature of energy. Considering some of them, one may find MS methodology, for instance, in Fong [38], Manera and Cologni [39], Hamilton [40], Joanne and Rafal [41], Luo et al. [42] and Chevallier [43]. One can follow also TAR studies in Jacobs et al. [44], Huang et al. [45], Lee and Chang [46], Phung [47], and Chevallier [43]. Secondly, none of these few papers above focus on renewable energy.

This paper specifically launches panel TAR models to reveal whether EU countries converge in production of primary solid biomass. The distinguishing features of this paper, then, are: (i) it employs one of the most important sources of renewable energy data, which is primary solid biomass, (ii) it follows linearity and nonlinearity tests of panel data for solid biomass, (iii) it carries out nonlinear methodology to estimate the parameters more efficiently than the linear counterparts, if in fact, the true data follows nonlinear process and (iv) it conducts convergence tests by considering regime shifts of panel data for solid biomass within given time period for EU, respectively.

2. Methodology

Let $z_{i,t}$ be defined by Eq. (1).

$$z_{i,t} = y_{i,t} - \overline{y}_t \tag{1}$$

where $y_{i,t}$ is per million solid biomass energy supply of ith country at time t and $\overline{y}_t$ is mean of panel at time t. Then, linear and nonlinear forms of $z_{i,t}$ are given by Eqs. (2) and (3), respectively, as indicated by Evans and Karras [48] and Beyaert and Camacho [36].

$$\Delta z_{i,t} = \partial_i + \rho_i z_{i,t-1} + \sum_{j=1}^{k} \theta_{i,j} \Delta z_{i,t-j} + \varepsilon_{i,t} \tag{2}$$

$$\Delta z_{i,t} = \left[\partial_{i(R1)} + \rho_{i(R1)} z_{i,t-1} + \sum_{j=1}^{k} \theta_{i,j(R1)} \Delta z_{i,t-j} \right]_{(z_{t-d} < r)} + \left[\partial_{i(R2)} + \rho_{i(R2)} z_{i,t-1} + \sum_{j=1}^{k} \theta_{i,j(R2)} \Delta z_{i,t-j} \right]_{(z_{t-d} \geq r)} + \varepsilon_{i,t} \tag{3}$$

where ∂_i, ρ_i and θ_i are the parameters of country i to be estimated and where Δ, $R1$, $R2$, d, r and $\varepsilon_{i,t}$ represent difference operator, Regime 1, Regime 2, delay parameter, threshold parameter and residual term of country i at time t, respectively. The residual term $\varepsilon_{i,t}$ is *i.i.d.* with zero mean and finite variance. In linear form denoted by Eq. (2), the parameters do not change, whereas in nonlinear form given by Eq. (3), parameters can change from Regime 1 to Regime 2 or vice versa. Eq. (3) follows TAR employing a nonlinear form when there are at least two states (regimes) with different linear forms (Tong and Lim [32], Tsay [33]). The unrestricted linearity tests are carried out through Eq. (2) while restricted version of this test is conducted by Eq. (4) at which the restriction is that $\rho_i=0$. This restriction yields unit root whereas unrestricted version of linearity just considers Eq. (2) employing the assumption of fixed parameters (Evans and Karras [48], Beyaert and Camacho [36]). The null hypotheses of linearity of (2) and (4) have alternative hypotheses of nonlinearity given by Eq. (3). If the estimated bootstrap probability values of t statistics obtained through linear equations are below the critical values, then, one may reject the null of linearity in favor of (3).

$$\Delta z_{i,t} = \partial_i + \sum_{j=1}^{k} \theta_{i,j} \Delta z_{i,t-j} + \varepsilon_{i,t} \tag{4}$$

If conclusion favors linearity, second test is convergence test following linear forms. The absolute convergence happens if the condition given by (5) is met and conditional convergence is realized if the condition indicated by (6) is hold (Evans and Karras [48], Beyaert and Camacho [36]).

$$0 < |\rho_i| < 1 \ \forall i \text{ and } \partial_i = 0 \ \forall i \tag{5}$$

$$0 < |\rho_i| < 1 \ \forall i \text{ and } \partial_i \neq 0 \text{ (for some } i\text{).} \tag{6}$$

Panel convergence tests by (5) and (6) are carried out through the assumption of cross sectional independence. What happens if there is cross sectional dependence in the panel? Chang [49], in this case, proposes bootstrap critical values for ρ, which is the percentage of bootstrap values of lower tail quantiles for t statistics, as is shown in Beyaert [50]. If model is found nonlinear, then considering Eq. (3), one may impose nonlinear TAR convergence tests for Regime 1 ($R1$) and Regime 2 ($R2$), separately following null and alternative hypotheses given in (7) and (8), respectively. Alternatively, one can run convergence tests for both

regimes considering (9) as depicted in Beyaert and Camacho [36].

$$H_0{:}\rho_{i(R1)} = 0\ \forall i \text{ against } \quad H_A : 0 < \left|\rho_{i(R1)}\right| < 1 \forall i \tag{7}$$

$$H_0{:}\rho_{i(R2)} = 0\ \forall i \text{ against } \quad H_A : 0 < \left|\rho_{i(R2)}\right| < 1\ \forall i \tag{8}$$

$$H_0{:}\rho_{i(Rs)} = 0\ \forall i \text{ against } \quad H_A : 0 < \left|\rho_{i(Rs)}\right| < 1\ \forall i \text{ and } \forall s \text{ as } s = 1,2 \tag{9}$$

This paper, accordingly, next section conducts (i) panel linearity versus panel nonlinearity tests, (ii) panel divergence against panel convergence tests in a linear model and (iii) panel unit root against panel convergence tests in a nonlinear model, following equations from (1) to (9), by observing quarterly data for renewable energy of solid biomass in European countries.

3. Data and estimation results

This section will cover, first, descriptive statistics for the data of EU countries' biomass production and visual inspections of related time series through figures and, later, carry out threshold autoregression analysis to depict the outcome whether or not EU countries converge in biomass energy production per million.

3.1. Data

The data for primary solid biomass energy supply of EU countries comes from IEA CD-ROM for Energy Balances of OECD Countries, 2010 Edition [1]. Solid biomass is measured in terms of ktoe (kilotonne of oil equivalent[1]). Panel 1971–2009 annual data set of primary solid biomass covers Austria, Denmark, Finland, France, Greece, Poland and Portugal. These seven EU countries are the available countries in CD ROM for the period 1971–2009. Annual 1982–2009 data includes ten EU countries of Austria, Belgium, Denmark, Finland, France, Greece, Norway, Poland, Portugal and Sweden. All variables are transformed into per million which refers solid biomass energy supply per million population. Population data for European countries is extracted through OECD [51].

Table 1 gives descriptive statistics for two panels. 1971–2009 panel statistics reveal that means of Poland and Greece are close to each other and that of Denmark, France and Portugal are roughly adjacent to each other. Austria and Finland seem to be far away from other five EU countries in the panel in terms of mean, standard deviation, maximum and minimum values. 1982–2009 panel data indicates that means of Poland and Greece are placed next to each other and that Denmark, France, Norway and Portugal may be grouped, yet their statistics are not too much close to each other. On the other hand, the descriptive statistical observations of Austria, Belgium, Finland and Sweden are the ultimate neighbor to each other among others. Finally, statistics reveal that means of Belgium, Greece and Poland are below OECD average. One may, on the other hand, claim that the descriptive statistics can give someone just preliminary and/or partial observations. Then, one may also need to observe the trends of the series through time. Fig. 1 yields series of per million solid biomass production for seven EU countries from 1971–2009. The uppermost line represents the trend of Finland's per million solid biomass production while the lowermost one shows that of Greece's per million solid biomass production.

Visual inspections from Fig. 1 indicates that, except France, Greece and Poland, all countries' series are upward sloping whereas Greece' series seems to be downward sloping and that the series of France and Poland tend to produce roughly horizontal lines. When one chooses the series randomly and estimates them, for instance, he or she obtains the equations of [$y = 0.7459x^2 - 10.862x + 783.35$] for Finland, [$y = 94.499e^{0.0464x}$] for Austria and [$y = -0.0069x^2 + 1.612x + 38.041$] for Greece, respectively.

Fig. 2 produces one with visual inspections for solid biomass production per million of 10 EU countries. Fig. 2 employs additionally the series of Sweden, Norway and Belgium for the period 1982–2009. One may estimate the equations of these countries' series as [$y = -0.2764x^2 + 22.8x + 478.33$], [$y = -0.2775x^2 + 11.205x + 131.56$] and [$y = 0.1517x^2 – 0.4369x + 4.6847$], respectively.

Table 1
Descriptive statistics of solid biomass energy supply (per million) in EU countries.

1971–2009	Mean	Standard dev.	Maximum	Minimum
Austria	273.8042	20.12873	488.2116	85.49613
Denmark	151.3815	15.25828	355.4708	25.99168
Finland	958.9404	39.3231	1433.463	647.6186
France	160.2646	2.538028	198.5236	134.2708
Greece	66.62525	2.996357	90.05749	45.1478
Poland	64.52912	5.933171	124.6199	21.92495
Portugal	172.8024	13.93019	284.7065	67.76538
OECD	82.53688	6.578008	125.4304	30.19575
1982–2009				
Austria	338.3009	15.4469	488.2116	179.2943
Belgium	40.15551	6.634605	119.6082	0.608748
Denmark	194.1983	14.44233	355.4708	104.5369
Finland	1041.487	45.17043	1433.463	699.202
France	159.9597	3.381518	198.5236	134.2708
Greece	73.61605	3.338358	90.05749	45.1478
Norway	217.5702	6.456331	300.9918	151.4052
Poland	78.48031	6.573405	124.6199	27.07897
Portugal	211.5508	13.52871	284.7065	78.8961
Sweden	732.7796	24.27681	922.4873	474.82
OECD	102.154	5.851092	125.4304	39.00762

3.2. Estimation results

This section has the purpose to reveal if biomass productions of EU countries converge or not. Table 2 introduces results of tests for (i) null hypothesis of panel linearity against panel nonlinearity and (ii) null hypothesis of panel divergence against panel convergence[2]. First column of Table 2 lists panel models estimated through either linear or nonlinear algebra. Second column gives the lag length to reach uncorrelated residuals. The lag selection estimation is done by feasible generalized least squares (FGLS). Third column yields bootstrap-p values for null hypotheses of linearity. Both restricted and unrestricted p values point out same results. Fourth and Fifth columns are the outcomes of linear convergence tests and nonlinear TAR convergence tests, respectively.

First four panels cover the period 1971–2009 and the next six panels consider period 1982–2009. Panel-1 rejects the null of linearity at the 5% level of significance. Therefore, Panel-1 indicates that panel solid biomass energy supply follows nonlinear TAR given by Eq. (3). The next step is to test divergence against convergence hypothesis. The last two columns imply that related nonlinear TAR model results in stationary process at one regime. Data yields non-rejection unit root under Regime 1 and rejection unit root during Regime 2 at 1% significance level. Hence, according to Panel-1, the per million primary solid biomass energy supply of Austria, Denmark, Finland, France and Portugal fluctuates around constant mean during Regime 2 whereas they,

[1] Toe unit can be transformed into other energy measurement units such as; 1 toe is equal to 41.84 GJ, 1 ktoe equals 41.84 TJ, 1000 ktoe is equal to 1 Mtoe and 1 Mtoe corresponds to 11.63 TW h (TeraWatt hours).

[2] Gauss codes of Beyaert and Camacho [36] with some modifications are utilized to obtain Table 2 statistics.

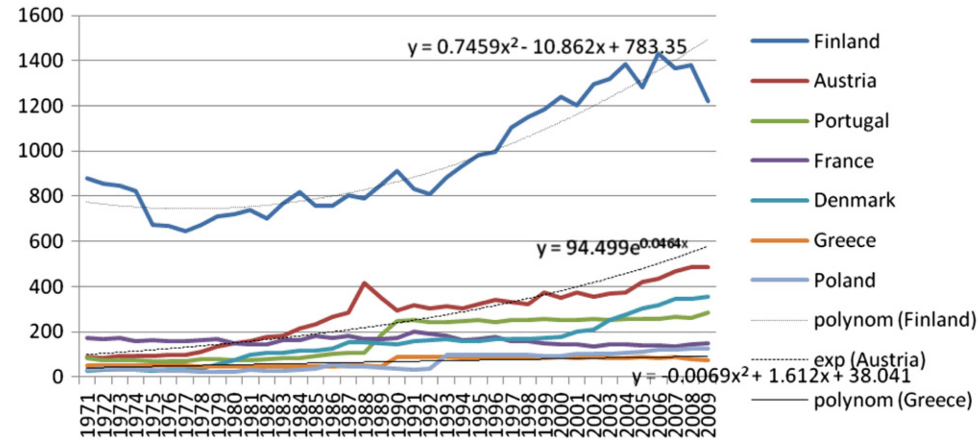

Fig. 1. Biomass Production Per Million EU-5, 1971–2009.

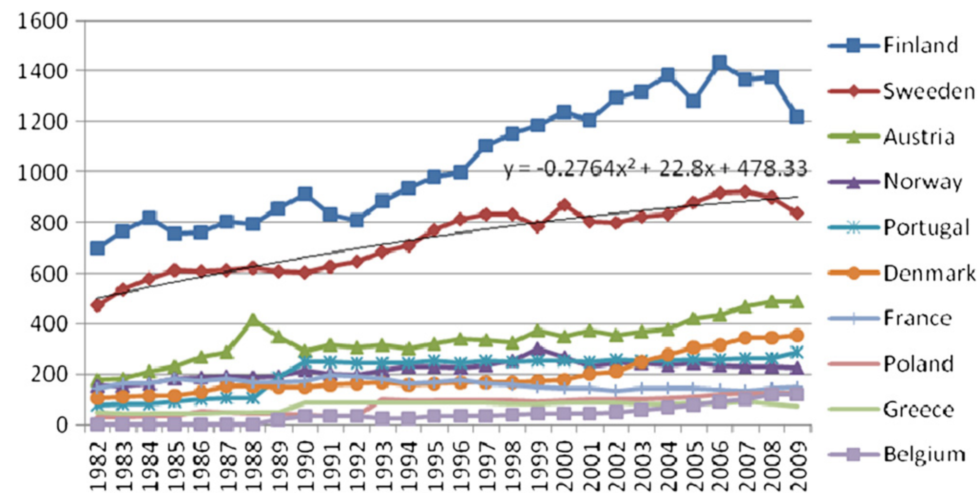

Fig. 2. Biomass Production Per Million EU-10, 1982-2009.

Table 2
Linear and TAR panel models for solid biomass energy supply (per million) in EU.

Panel[a]	Lag (k)	Null of linearity test (bootstrap-p)		Null of linear divergence test (bootstrap-p)	Null of nonlinear TAR divergence test (bootstrap-p)	
		Unrestricted	Restricted		Regime 1	Regime 2
Panel-1	1	0.0180	0.0120	–	0.3640	0.0050
Panel-2	1	1.0000	1.0000	0.1710	–	–
Panel-3	1	1.0000	1.0000	0.1480	–	–
Panel-4	1	1.0000	1.0000	0.1560	–	–
Panel-5[b]	1	0.0110	0.0160	–	0.0640	0.1280
Panel-6	1	0.5670	0.5110	0.3440	–	–
Panel-7	1	0.9250	0.8170	0.3030	–	–
Panel-8	1	1.0000	1.0000	0.3140	–	–
Panel-9	1	1.0000	1.0000	0.2970	–	–
Panel-10[b]	1	1.0000	1.0000	0.3380	–	–

[a]The periods and countries for which panels employ are as follows:
Panel-1 1971–2009 Austria, Denmark, Finland, France and Portugal.
Panel-2 1971–2009 Austria, Denmark, Finland, France, Portugal and Greece.
Panel-3 1971–2009 Austria, Denmark, Finland, France, Portugal and Poland.
Panel-4 1971–2009 Austria, Denmark, Finland, France, Portugal, Greece and Poland.
Panel-5 1982–2009 Austria, Denmark, Finland, France and Portugal.
Panel-6 1982–2009 Austria, Belgium, Denmark, Finland, France and Norway.
Panel-7 1982–2009 Austria, Belgium, Denmark, Finland, France, Norway and Sweden.
Panel-8 1982–2009 Austria, Belgium, Denmark, Finland, France, Norway, Sweden and Portugal.
Panel-9 1982–2009 Austria, Denmark, Finland, France, Greece, Norway, Sweden, Portugal and Poland.
Panel-10 1982–2009 Austria, Belgium, Denmark, Finland, France, Greece, Norway, Sweden, Portugal and Poland.

[b] Lag selection is 2 ($k=2$) by FGLS. However, TAR Panel with $k=2$ yields singular matrix. Therefore the linear and nonlinear TAR Panels are run with $k=1$.

as panel, suffer permanent effects from random shocks under Regime 1. When, on the other hand, Greece and/or Poland are added to Panel-1 data, the data diverges with at least one country. In addition to countries of Panel-1, Panel-2 adds Greece, Panel-3 includes Poland and Panel-4 appends both Greece and Poland. Later three panels including Greece and/or Poland show biomass-level divergence and hence they experience unit root process. One may recall from Table 1 that both Greece and Poland's individual time series of solid biomass energy supply are below OECD average of solid biomass energy supply while biomass supply of Austria, Denmark, Finland, France and Portugal are above OECD average. This descriptive statistics might be a support why Panel-1 reaches convergence and why Panel-2, Panel-3 and Panel-4 do not. One may notice as well that, when Greece and/or Poland are attached to Panel-1, the panel data succeeds linear model (2) instead of TAR model (3). The available data for the period 1971–2009 covers seven EU countries. To be able to reach more EU countries, this paper launches additionally 1982–2009 period.

For instance, Panel-10 keep tracks of period 1982–2009 for solid biomass energy generation of Austria, Belgium, Denmark, Finland, France, Greece, Norway, Poland, Portugal and Sweden. Except Panel-5, the 1982–2009 panels exhibit linearity rather than nonlinearity.

Panel-5, on the other hand, rejects linear form at 5% significance level. One sees that both Panel-1 and Panel-5 favor nonlinearity and convergence for the same countries. On the other hand, following nonlinear TAR model, the Panel-5 data refers convergence during Regime 1 at 10% level. The divergence in solid biomass energy supply of Panel-5 is not rejected at 10% level during Regime 2. Or one may claim that the divergence of Panel-5 during Regime 2 may occur due to relatively less observation in comparison with the observations of Panel-1. As in the case of 1971–2009 panel studies of this paper, 1982–2009 panel studies yield also the output that the nonlinearity and convergence occur only in panel data for Austria, Denmark, Finland, France and Portugal within given period(s) and available EU countries. Therefore, 1982–2009 panels imply that, when Belgium, Greece, Norway, Poland and Sweden are added individually or jointly to the Panel-5, the resulting output is both linearity and divergence in per million biomass energy supply. This divergence may come from differences in GDP and renewable energy development policies and other country specific effects among EU countries as indicated by Gan and Smith [52]. Krausmann et al. [53] state that, within last century, in comparison with population growth, the growth in usage of biomass decline while that of metal ores, industrial minerals and construction minerals increase and that, especially after WWII, there is a shift from biomass usage towards mineral materials. This shift might be due to increase in material productivity, which, in turn, might arise from relative decline in consumption growth of biomass. BTG [54] underlies the differences in biomass production as (i) carbon stock differences, (ii) the differences in Forest Certification Systems (FSC) and Program for the Endorsement of Forest Certification (PEFC) and (iii) present voluntary system and EU based obligatory system.

One needs statistical details and interpretations of nonlinear TAR models of Panel-1 and Panel-5. Table 3[3] gives transition variables delay parameters, threshold values and regime classifications for Panel-1 and Panel-5. Transition variable of Panel-1 is Denmark. The delay parameter is determined as 1. Therefore, log of Eq. (10) for Denmark produces the variable of difference between growth rate of per million biomass energy supply of Denmark and average growth rate of per million biomass energy supply of Panel-1.

$$trv_{i,t} = z_{i,t} - z_{i,t-1} \tag{10}$$

Threshold value ($trv_{i,t}$) of 11.5298 implies that growth rate of Denmark per million biomass energy supply is above the mean of panel per million biomass energy supply by 11.5298 unit. Regime 1 falls within interval at which ($trv_{i,t}$) is below 11.5298 units and Regime 2 consists of observations for which ($trv_{i,t}$) is above 11.5298 units. Regime 1 consists of 86.11% of panel observations whereas Regime 2 corresponds to 13.89% of data. In Panel-5, the transition variable is Portugal with delay parameter of 1 and threshold value of −4.2317. Regime 1 and Regime 2 match up to observations below threshold with 16.00% and above threshold with 84.00%, respectively.

Considering the differences between Panel-1 and Panel-5, one needs to determine which panel should be taken into account mainly in TAR convergence tests. One prefers Panel-1 since (i) Panel-1 has longer time span than Panel-5, and (ii) although lag length (k) of Panel-5 is determined as 2 by FGLS, since Gauss TAR optimization procedure results in singular matrix with lag 2, this paper runs Panel-5 with lag 1 to see just roughly if Panel-5 yields nonlinearity and convergence, as well. In other words to say, Panel-5 is conducted for comparison purpose to be able to verify that 1971–2009 panel of Austria, Denmark, Finland, France and Portugal found nonlinear and stationary is also nonlinear and stationary in period 1982–2009. Panel-1 dominates Panel-5 due to lag reason given above, as well. Therefore, finally, one can conclude that Austria, Denmark, Finland, France and Portugal converge to common trend during Regime 2 within period 1971–2009. One however should emphasize here that this convergence is partial not global, as is seen in Table 2. The Panel-1 panel data, accordingly, does follow stochastic trend during Regime 1 and does yield deterministic trend during Regime 2. One also needs to underline that stationary period in Regime 2 refers only small part of total observations. It should be discussed on empirical importance of significant rejection of unit root at 13.89 percentages of total observations. This point is, however, beyond the scope of this paper.

Table 3
Transition variable and threshold values of TAR models for biomass energy supply.

Panel[a]	Transition variable	Delay parameter	Threshold Value	Regime classification	
				Regime 1	Regime 2
Panel-1	Denmark	1	11.5298	86.11%	13.89%
Panel-5[b]	Portugal	1	−4.2317	16.00%	84.00%

[a] The periods and countries for which panels employ are as follows:
Panel-1 1971–2009 Austria, Denmark, Finland, France and Portugal.
Panel-5 1982–2009 Austria, Denmark, Finland, France and Portugal.

[b] Lag selection is 2 ($k=2$) by FGLS. However, TAR Panel with $k=2$ yields singular matrix. Therefore the nonlinear TAR Panel is carried out with $k=1$.

4. Conclusion

This paper considers if biomass energy supply of European countries follow linear or nonlinear threshold autoregressive (TAR) process. By employing annual 1971–2009 and 1982–2009 periods with 10 different panel data sets, this paper also aims at having statistical finding whether EU biomass energy supply is stationary or not. To this end, in this work, primary solid biomass energy supply per million of European countries are employed

[3] Table 3 statistics are produced through Gauss codes of Beyaert and Camacho [36] with some modifications.

and launched to test first null hypothesis of linearity against nonlinearity and secondly that of divergence against convergence. Initially, the panel data for Austria, Denmark, Finland, France and Portugal is employed and found nonlinear and partially converged. The divergence happens in Regime 1 period, whereas stationarity occurs during Regime 2 period. In other words to say, Austria, Denmark, Finland, France and Portugal exhibit convergence in production of biomass energy supply during Regime 2 observations within period 1971–2009. For the same time period, when Greece and/or Poland are added to initial five EU countries, the result is linear and nonstationary process. To expand the number of EU counties to be employed in a panel, this work runs period 1982–2009, as well. 1982–2009 panel data indicates also that Austria, Denmark, Finland, France and Portugal follow nonlinear TAR and stationary path, and, that if Belgium, Greece, Norway, Poland and Sweden join panel data of Austria, Denmark, Finland, France and Portugal, individually or jointly, the resulting point is linearity and divergence. One may imply that there are differences in production of biomass energy supply between the group of Austria, Denmark, Finland, France and Portugal and group of Belgium, Greece, Norway, Poland and Sweden in terms of technological, institutional, educational and political constant and/or trend of the related individual time series.

This result may bring about some policy proposals. These proposals might cover some required adjustments for renewable energy regulations among EU countries. In the short and medium terms, investment tax incentives and sectoral subsidies, i.e. in agriculture, may play crucial role within this framework. Research and developments on biomass technology may result in lower costs through increasing efficiency in production of biomass, most likely not in the short run but in the long run. These may incentivize biomass usage against traditional fossil fuel oil with relatively lower price.

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